Can education explain the vote for Trump in the 2024 elections ? A spatial analysis

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Abstract

The 2024 U.S. presidential election saw Donald Trump secure a second term, raising questions about the structural factors influencing his electoral success. While education has been widely recognized as a key determinant of voting behavior, its role in the 2024 election, particularly in the presence of spatial dependencies, remains underexplored. This study examines the relationship between educational attainment and Trump's vote share across the lower 48 U.S. states, employing spatial econometrics to account for geographic spillovers in voting behavior. The results confirm a negative correlation between education and Trump support, reinforcing findings from previous elections. However, spatial models reveal that a state's education level also influences the voting behavior of neighboring states, highlighting the importance of regional effects. Additionally, while economic and demographic factors such as GDP, racial composition, and gender ratio contribute to voting preferences, their impact is weaker than that of education. These findings underscore the necessity of spatial approaches in electoral studies and suggest that improving access to higher education could have long-term implications for political alignments in the United States.

Keywords: Trump voting, U.S. elections, education, spatial econometrics, voting behavior, regional spillovers, political geography

1 Introduction

On 5th November 2024, Americans elected their new president. The controversial businessman Donald Trump, already president from 2016 to 2020, won his second term ahead of Kamala Harris, vice-president under President Biden. Announced as close as his 2016 victory over Hillary Clinton, Trump ended up winning the election by a large margin (312 vs. 236 electoral votes). This significant lead was achieved by the fact that Trump won every single swing state, decisive battlegrounds where the outcome can be determined by a few thousand or even a few hundred votes.

In order to attract these crucial votes, President Trump adopted highly polarizing positions on immigration throughout his campaign. Trump repeatedly expressed xenophobic opinions on immigrants, claiming they were "poisoning the blood of our country." He went further, alleging that in Springfield, Ohio, Haitians were "eating the dogs" of residents. Despite the misinformation surrounding these claims, Trump gained popularity among ethnic minorities, particularly Hispanics. Trump also benefited from the strategic support of billionaire Elon Musk, who played a central role in spreading Trump's views and strengthening his campaign. This support was both financial - Musk contributed $260 million to Trump's campaign (CNN, 2024) - and ideological, through his social media platform X (formerly Twitter). While some studies suggest that Twitter had little effect on Trump's success in 2016 (Fujiwara et al., 2020), emerging evidence indicates that the situation in 2024 was different[1]. Leveraging Brandolini's law, also known as the bullshit asymmetry principle, Musk facilitated a shift in the Overton window, making misinformation and xenophobic rhetoric more politically acceptable to the public.

[1] *Comment Elon Musk a dopé la campagne de Donald Trump*, Brieuc Beckers, Léa Sanchez, Elisa Bellanger, and Adrien Vande Casteele, *Le Monde*, 08 November 2024

In this context, this paper seeks to determine whether education attainment can explain Trump's electoral success in 2024. This research question is based on the underlying assumption that individuals with higher education levels may be less inclined to vote for Trump, as they tend to be more culturally open and less susceptible to misinformation. Several studies suggest that people with higher education levels exhibit greater digital literacy, making them less vulnerable to fake news (Pop and Ene, 2019). Furthermore, cultural openness - particularly regarding diversity and globalization - is often associated with higher educational attainment (Kaufman et al., 2016). However, recent studies indicate that in the last two American elections, having a college degree was only a significant factor for white voters (Schaffner et al., 2018). This paper seeks to assess whether this pattern can be generalized to the entire U.S. population in 2024.

Voting determinants are complex, particularly in the United States, where socio-economic and racial dynamics intersect in a unique ways. It is therefore insufficient to examine education alone. In addition to educational attainment, this study incorporates a range of socio-ethno-demographic variables to provide a more comprehensive analysis of Trump voting patterns. Given that political behavior is often spatially clustered, with neighboring states exhibiting similar voting trends, we employ spatial econometrics to determine how the geographic component influences the Trump vote. To achieve this, we first present and conduct a statistical analysis of the key explanatory variables. Next, we introduce the econometric methodology, outlining the advantages of incorporating spatial dependencies. Finally, we present the results and implications of our findings.

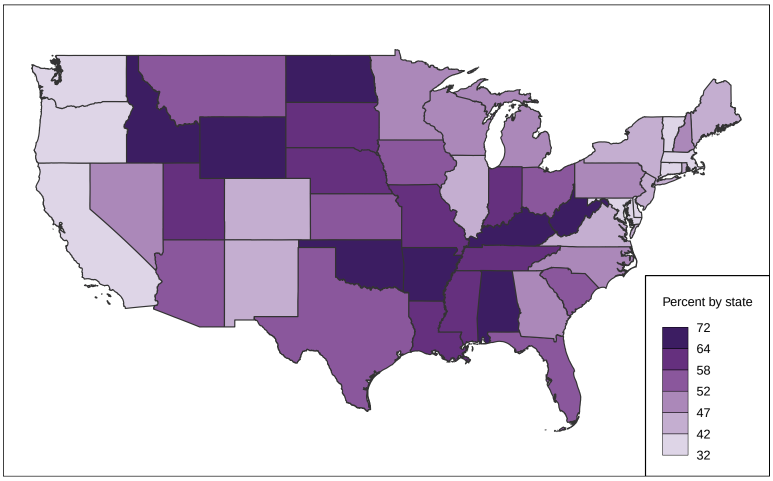
2 Data

2.1 Trump voting across the lower 48 states

Figure 1 illustrates the spatial distribution of Donald Trump's vote share across U.S. states. Trump's strongest support is evident in the South (e.g., Alabama, West Virginia, and Tennessee), the Great Plains (e.g., North Dakota, South Dakota, and Nebraska), and parts of the Mountain West (e.g., Wyoming and Idaho). These areas, traditionally Republican strongholds, continue to show strong loyalty to the party. On the other hand, states along the West Coast (e.g., California, Oregon, and Washington) and the Northeast (e.g., Massachusetts, New York, and Vermont) exhibit significantly lower levels of support, reinforcing their status as Democratic bastions. The Midwest presents a more mixed landscape, with Ohio and Indiana showing stronger Trump support, while Illinois and Minnesota lean Democratic.

A crucial aspect of this distribution is the role of swing states, which have historically decided presidential elections. Several key battleground states, such as Pennsylvania, Michigan, and Wisconsin, were pivotal in Trump's victory. The Sun Belt states (Arizona, Georgia and North Carolina) have also emerged as highly contested areas, with changing demographics, particularly growing urban and suburban populations.

Figure 1: Spatial distribution of Trump's vote



2.2 *The factors behind Trump's vote*

Voting preferences in the United States are shaped by a combination of socio-economic, demographic, and geographic factors. While no single variable determines electoral outcomes, well-documented trends suggest that certain groups and economic conditions are more aligned with either the Democratic or Republican parties. Despite his controversial rhetoric on immigrants, Donald Trump has managed to extend his reach among black, Hispanic and Asian voters. Estimates suggest that in 2024, Donald Trump won the support of 13% of black voters (up from 12% in 2020 and 8% in 2016), 39% of Asian voters (up from 34% in 2020 and 28% in 2016) and, notably, 46% of Hispanic voters (up from 32% in 2020 and 28% in 2016). The increase in support among Hispanic voters is particularly noticeable among young people and men, with the Republican candidate attracting a record 55% of the Hispanic male vote (Lassalle, 2023).

2.2.1 *Education and Gender: A Strong Democratic Affinity*

Higher levels of education have consistently been associated with Democratic voting patterns. This study utilizes the proportion of the population (25 years and older) with at least a bachelor's degree as an indicator of educational attainment, based on the most recent data from the U.S. Census Bureau. Research has shown that individuals with higher education levels are more likely to support Democratic candidates, influenced by greater exposure to diverse perspectives, progressive social values, and stronger support for government intervention in economic and social policies (Center, 2018). Closely related to educational attainment, gender also plays a significant role in electoral behavior. This study employs the gender ratio (the number of males per 100 females) as a key demographic variable. Research has shown that women are more likely to vote for Democratic candidates, driven by policy preferences on issues such as reproductive rights, healthcare, and social welfare (Schaffner et al., 2018).

2.2.2 *Economic Factors and Republican Support in Struggling Regions*

Economic conditions have long been a crucial determinant of political behavior. This study measures economic performance using Gross Domestic Product (GDP), reported in billions of dollars. While GDP serves as a useful indicator of a state's economic strength, it does not account for disparities in wealth distribution, cost of living, or individual income levels. Despite these limitations, research suggests that states with higher GDP tend to lean Democratic, as economic prosperity is often linked to urbanization, technological development, and a more diverse labor force (Margalit, 2019). In contrast, economically struggling states, particularly in the post-industrial Midwest and rural South, have become strongholds of Republican support, driven by economic discontent, concerns over globalization, and opposition to progressive economic policies (Autor et al., 2016).

2.2.3 Demographics and immigration

Beyond economic conditions, demographic composition is a critical factor in voting behavior. This study includes three demographic indicators: the proportion of lawful permanent residents (LPR), the Hispanic and Black population share. The proportion of LPRs captures the immigrant population, an important group in shaping electoral trends. Historically, states with a higher share of immigrants tend to vote Democratic, as immigration policies, social inclusion, and minority rights have been central to the Democratic candidates (Hainmueller and Hopkins, 2014). Similarly, the proportion of Hispanic residents is an important demographic variable, given the growing influence of Latino voters in U.S. elections. While Hispanic political preferences are not fixed, past research has shown a general Democratic preference, particularly among first- and second-generation immigrants. However, recent shifts have indicated that economic concerns, religious conservatism, and outreach efforts by Republican candidates have led to an increase in Hispanic support for the Republican party in certain regions (Corral and Leal, 2020). The proportion of Black residents, is another crucial demographic factor influencing voting behavior. Black voters have overwhelmingly supported Democratic candidates for decades, a trend rooted in historical civil rights policies, economic inequality, and party alignment on racial justice issues (Dawson, 1995 ; Philpot, 2018).

2.3 Descriptive analysis

Table I, Figure 2 and 3 reveals significant heterogeneity across states. In terms of GDP, California, Texas, and New York stand out as clear outliers, with significantly higher economic output than other states (Figure 2b). According to Table I, the mean GDP across states is 437.4 billion, but the median is much lower at 257 billion, highlighting the skewed distribution driven by these high-performing states (Figure 3b). California, in particular, has the highest GDP ($3,137$ billion), benefiting from a strong technology sector in Silicon Valley, a dominant entertainment industry in Los Angeles, and a robust agricultural sector in the Central Valley. Texas follows, driven by the oil, energy, and technology industries, while New York benefits from being home to Wall Street, a global financial hub.

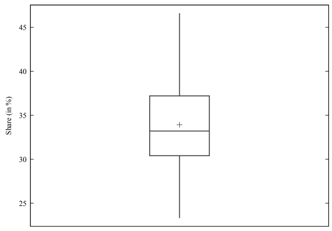
Table I: Descriptive Statistics of explanatory variables

Variable	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**
GDP (in billions of USD)	437.40	257.00	557.53	34.00	3137.00
No. of legal Residents (Per 1M inhabitants)	1882.80	1525.00	1473.40	105.00	5934.00
Gender ratio	97.41†	97.18	2.62	93.00	103.37
Black Population (%)	10.48	7.55	9.17	0.47	36.44
Hispanic Population (%)	12.80	10.51	10.31	1.94	47.74
Educational attainment (%)	34.03	33.65‡	5.50	23.30	46.60

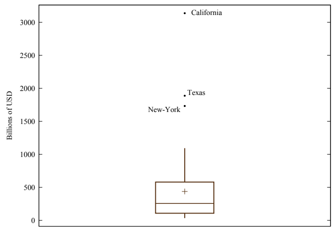
†*In 2020, on average, there were 97.41 males for 100 females in the United States*
‡*In 2023, of the population aged 25 and over, half the States had more than 33.65% of their population with a bachelor's degree or higher, while the other half had less than 33.65%*

Regarding demographics variables, historical migration patterns help explain the concentrations of Black and Hispanic populations in certain states. The Black population is particularly high in Mississippi, Georgia, and Louisiana, with Mississippi showing the highest proportion at 36.44% (Figure 2d ; Table I). This distribution reflects the painful legacy of the transatlantic slave trade and plantation economy that historically defined the Deep South. Many Black Americans remained in these states following the Civil War, and although the Great Migration saw millions move to northern cities in the 20th century, the South remains home to a significant share of the Black population. Similarly, the Hispanic population is heavily concentrated in New Mexico, Texas, and California (Figure 2e). The mean proportion of Hispanic residents is 12.8%, but the distribution is skewed, with New Mexico showing a striking 47.74% (Figure 3e ; Table I). These patterns are influenced by both historical ties to Mexico and Spain and more recent immigration trends, as these states were once part of Spanish and Mexican territories.

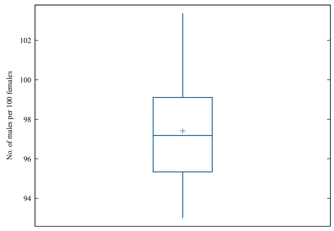
Figure 2: Boxplots of explanatory variables



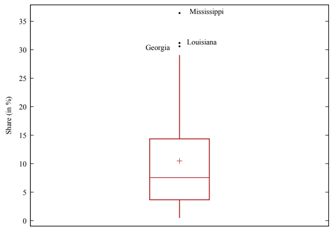
(a) Share of the population (25 years and over) who have completed a bachelor degree or higher, 2023 (%)



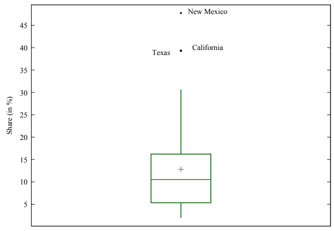
(b) GDP in 2019 (in billions of USD)



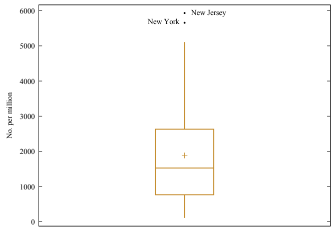
(c) Gender ratio in 2020 (No. of males per 100 females)



(d) Proportion of people considered black in 2020 (%)



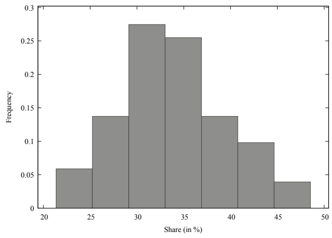
(e) Proportion of people considered hispanic in 2020 (%)



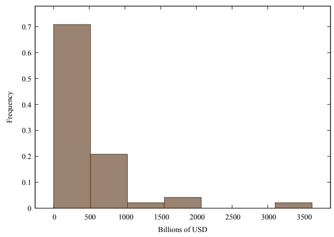
(f) Lawful permanent residents in 2022 (No. per million inhabitants)

Educational attainment also exhibits significant disparities. The mean proportion of individuals holding a bachelor's degree or higher is 34.03%, with a median of 33.65% (Table I). However, as the Figure 3a shows, some states far exceed this figure, largely due to the presence of elite universities and strong economies that attract highly skilled professionals. On the other hand, states with lower levels of educational attainment often have rural economies or historical inequalities in access to higher education. Finally, the gender ratio, which averages 97.41 males per 100 females, remains relatively stable across states (Figure 3c).

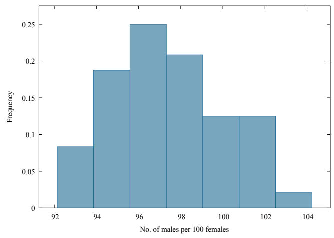
Figure 3: Histograms of explanatory variables



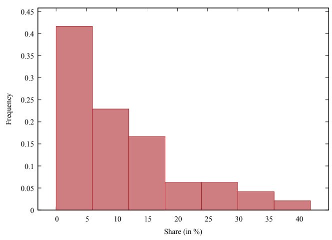
(a) Share of the population (25 years and over) who have completed a bachelor degree or higher, 2023 (%)



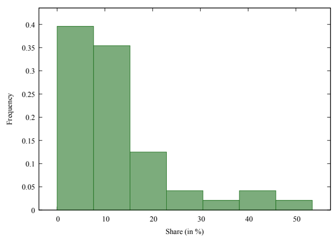
(b) GDP in 2019 (in billions of USD)



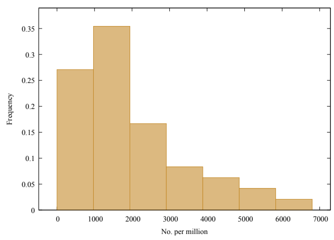
(c) Gender ratio in 2020 (No. of males per 100 females)



(d) Proportion of people considered black in 2020 (%)



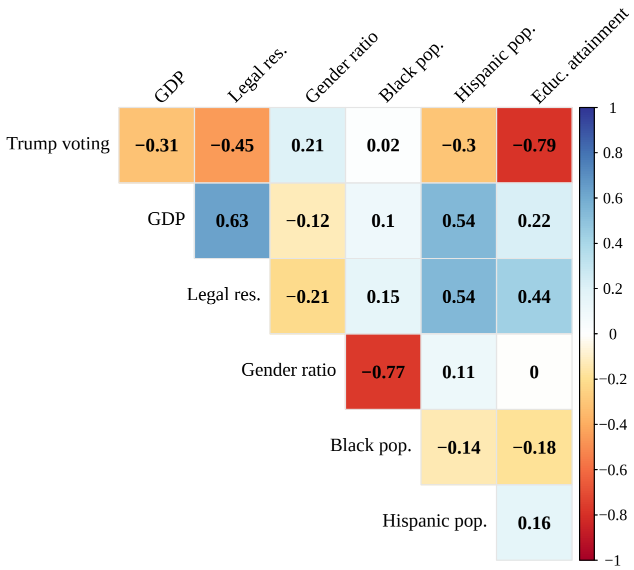
(e) Proportion of people considered hispanic in 2020 (%)



(f) Lawful permanent residents in 2022 (No. per million inhabitants)

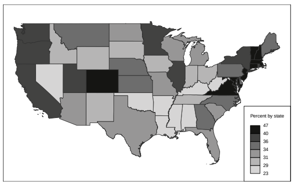
Figures 5a, 5b, and 5f illustrate that states with higher levels of education tend to have more diverse and economically prosperous populations, a factor traditionally associated with Democratic-leaning voters. The correlation matrix confirms this trend, showing a strong negative correlation (-0.79) between education levels and Trump voting, reinforcing the established link between higher educational attainment and Democratic support (Figure 4). This result is in line with previous research, which emphasises that education favours progressive attitudes and a preference for government intervention in social policies (Borjas, 2018).

Figure 4: Correlation matrix

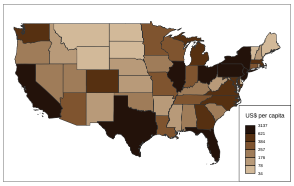


The relationship between economic prosperity and voting behavior is also evident. The correlation matrix highlights a negative association (-0.31) between GDP and Trump voting, suggesting that wealthier states were less likely to support the Republican candidate. This observation supports existing literature on how economic distress influences political preferences, particularly in regions affected by deindustrialization (Autor et al., 2016). Indeed, economically struggling areas, notably in the Rust Belt and rural America, have become strongholds of Republican support, as economic insecurity and job losses have fueled skepticism toward globalization and elite political institutions. On the other hand, the correlation between GDP and legal permanent residents (0.63) suggests that economically dynamic states attract more immigrants, a demographic group that historically leans Democratic (Figure 4). The disparity in GDP, displayed in Figures 2b and 3b, exhibits a highly skewed distribution, with a few states such as California, Texas, and New York significantly surpassing others in economic output. Furthermore, these are the same states where the number of legal residents is high, reinforcing the argument that economic prosperity drives immigration (Peri, 2012).

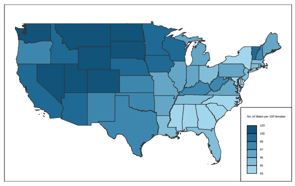
Figure 5: Spatial distribution of explanatory variables



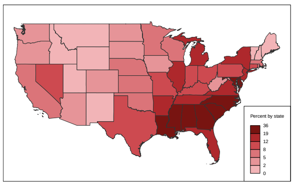
(a) Share of the population (25 years and over) who have completed a bachelor degree or higher, 2023 (%)



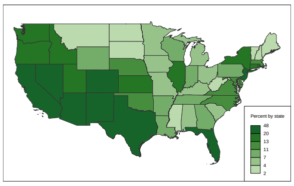
(b) GDP in 2019 (in billions of USD)



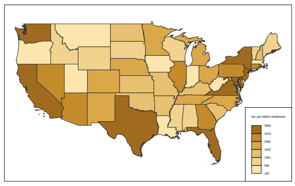
(c) Gender ratio in 2020 (No. of males per 100 females)



(d) Proportion of people considered black in 2020 (%)



(e) Proportion of people considered hispanic in 2020 (%)



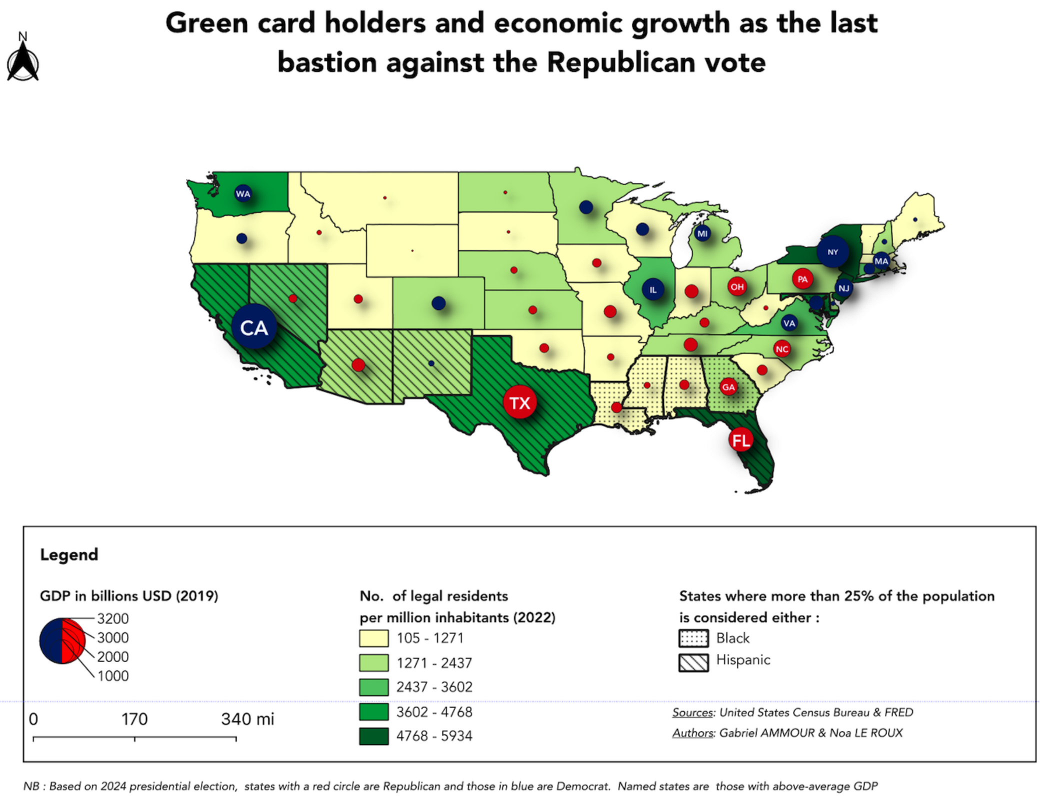
(f) Lawful permanent residents in 2022 (No. per million inhabitants)

Beyond economic factors, demographic composition also plays a crucial role in shaping electoral outcomes. The negative correlation (-0.45) between lawful permanent residents and Trump voting suggests that states with larger immigrant populations are less likely to support Republican candidates, a pattern widely observed in electoral studies (Abrajano and Hajnal, 2015). Similarly, the proportion of Hispanic residents is negatively correlated with Trump voting (-0.30), reflecting the broader national trend of Hispanic voters leaning Democratic, despite some shifts in the last election. These results align with the observed positive correlation (0.54) between lawful permanent residents and the Hispanic population, confirming that immigration is an important determinant of electoral preferences (Figure 4).

Another notable trend emerges regarding gender dynamics. The correlation matrix reveals a positive association (0.21) between the gender ratio and Trump voting, suggesting that states with a higher proportion of men were more inclined to support the Republican candidate. This pattern is consistent with research on gender differences in political preferences, where men have historically shown stronger support for conservative candidates due to economic insecurity, views on social issues, and political messages (Inglehart and Norris, 2000). Additionally, the strong negative correlation (-0.77) between the gender ratio and the proportion of Black residents suggests that states with a higher share of Black residents tend to have more women. This pattern may be linked to broader socio-demographic factors, including disparities in mortality and incarceration rates, which disproportionately affect Black men and contribute to gender imbalances in certain states (Western and Pettit, 2010).

Map shown in Figure 6 provides an analysis of the correlation between green card holders, economic growth and voting patterns in the 2024 US Presidential election. The map shows the distribution of legal residents per million inhabitants in different states, combined with economic performance measured by GDP (2019). It also highlights states where more than 25% of the population identifies as Black or Hispanic.

Figure 6: Green card holders and economic growth as the last bastion against the Republican vote



The map suggests a geographic and demographic pattern in which states with higher GDP, particularly California, Texas, Florida and New York, also have significant numbers of legal residents. The colour code differentiates the density of legal residents, while the hatched areas indicate states with a large number of minorities. The interactions between economic weight, demographic diversity and political alignment are highlighted by the red and blue circles representing Republican and Democratic strongholds. The map suggests that states with a strong economy and a high concentration of immigrant populations tend to resist Republican voting trends. On the other hand, states with a lower density of legal residents seem more inclined to support Republicans. These findings are consistent with the previous discussion.

3 Econometric methodology

The econometric approach aims to explain the proportion of votes for Trump by state in 2024, by considering potential interactions between states. Spatial econometrics takes into account spatial heterogeneity, which refers to the diversity of behaviour according to geographical location, and spatial autocorrelation, which examines the level of interaction between spatial units, in this case States.

The weight matrix (W) is an essential tool for structuring spatial relationships by defining the neighbours of each state. Different specifications of this matrix are possible:

- The Queen matrix considers as neighbours all states sharing a border or a common point.
- The Tower matrix restricts the neighbourhood to states sharing a common border.
- The k nearest neighbours matrix is based on geographical proximity, with no need for physical contiguity.

Before estimating the models, it is essential to test for spatial autocorrelation using the Moran index (I), which tests the null hypothesis of no autocorrelation. The Moran diagram shows the relationship between the values of a variable and the average values of its neighbours. In addition, LISA (Local Indicators of Spatial Association) can be used to measure the intensity and significance of the local dependence between the value of a variable and the values of that variable in neighbouring spatial units.

Several models can be considered, taking into account endogenous, exogenous and unobservable effects:

- The **Spatial Autoregression Model (SAR)** captures endogenous spatial effects, where a state's dependent variable is influenced by that of its neighbours. This model is formalised by the following equation :
$$y = \rho W y + X\beta + \varepsilon$$
where ρ represents the intensity of this influence, y is the dependant variable, W the spatial weight matrix, Xexplanatory variables, and ε the error term.
- The **Spatial error model (SEM)** takes into account the impact of the residuals of one state on those of its neighbours. It is formalised as :
$$y = X\beta + u, \quad u = \lambda W u + \varepsilon$$
where λ measures the spatial autocorrelation of errors.
- The **Spatial Durbin Model (SDM)** includes both the explanatory variables and the dependent variable spatially shifted, making it possible to capture the direct and indirect effects of the explanatory variables. It is formulated as follows:
$$y = \rho W y + X\beta + W X\theta + \varepsilon$$
where θ represents exogenous interactions.
- The **Spatial Lag of X (SLX)** model is used to identify the presence of exogenous spatial effects, where a state's dependent variable is influenced by the observable characteristics of its neighbours. Its form is given by :
$$y = X\beta + W X\theta + \varepsilon$$

The selection of the most appropriate model can be based on Lagrange tests and on Elhorst's methodology, which proposes a mixed approach.

4 Spatial model estimation

4.1 Measuring global spatial autocorrelation

Table II: Moran tests for different spatial weight matrices

Matrix	Standard Moran test			Monte-Carlo Simulation	
	I Moran	Statistic z	p-value	Statistic	p-value
Queen	0,386	4,148	1,678e-05	0,386	0,001
1 nearest neighbour	0,532	3,161	7,863e-04	0,532	0,001
3 nearest neighbours	0,452	4,436	4,586e-06	0,452	0,001

Note : All the tests are significant at the 1% level. The Monte-Carlo simulation was carried out with 999 permutations.

Table II presents the Moran tests, carried out to evaluate spatial autocorrelation across different weight matrices. The results reveal a significant spatial dependence. The positive Moran index (I) in all cases suggests that areas with similar values tend to be grouped together geographically. More specifically, for the Queen matrix, the Moran index is 0.386, with a z statistic of 4.148 and a p-value of 1.678e-05, confirming significant spatial autocorrelation at the 1% threshold.

Similarly, the matrices based on nearest neighbour (0.532) and three nearest neighbours (0.452) show positive Moran indices and p-values below 0.001, reinforcing the idea of a non-random spatial structure. The Monte-Carlo simulations used to validate these results came to the same conclusions, with p-values of 0.001 for all the matrices, which supports the hypothesis that the groupings observed are not due to chance, but reflect a real spatial dependency.

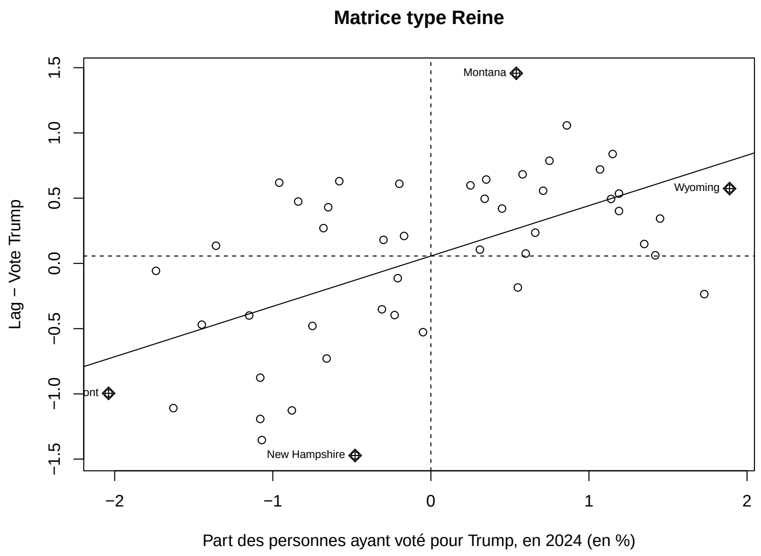


Figure 7: Moran index for the Queen matrix

Figures 8, 9, and 7 present Moran diagrams illustrating the spatial autocorrelation of the vote for Trump in 2024 under three different spatial weighting matrices: NN1 (nearest neighbour), NN3 (three nearest neighbours) and the Queen type matrix. In all three cases, the positive slope of the regression line indicates an overall positive spatial autocorrelation, suggesting that geographically close states tend to exhibit similar voting behaviour.

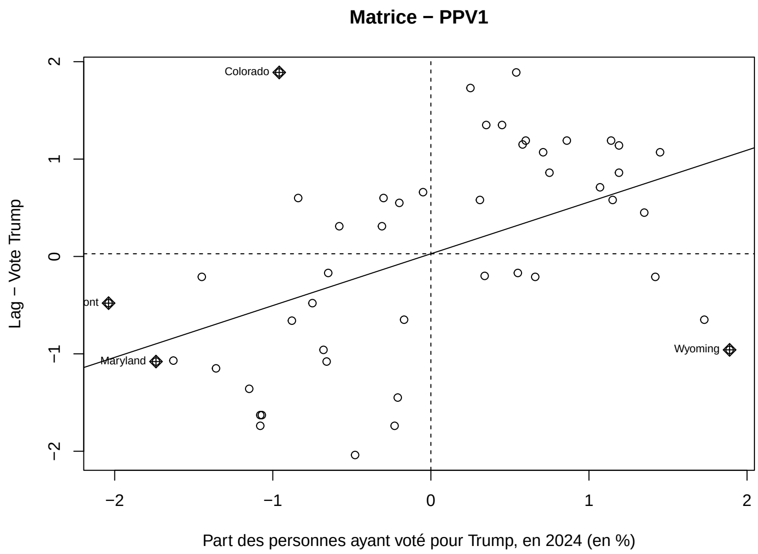


Figure 8: Moran index for the NN1 matrix

New Hampshire systematically stands out as an atypical point in the three configurations, exhibiting electoral behaviour that differs from its immediate neighbours. However, some states, such as Wyoming, show a high degree of consistency with their neighbours, particularly visible in the NN1 matrix.

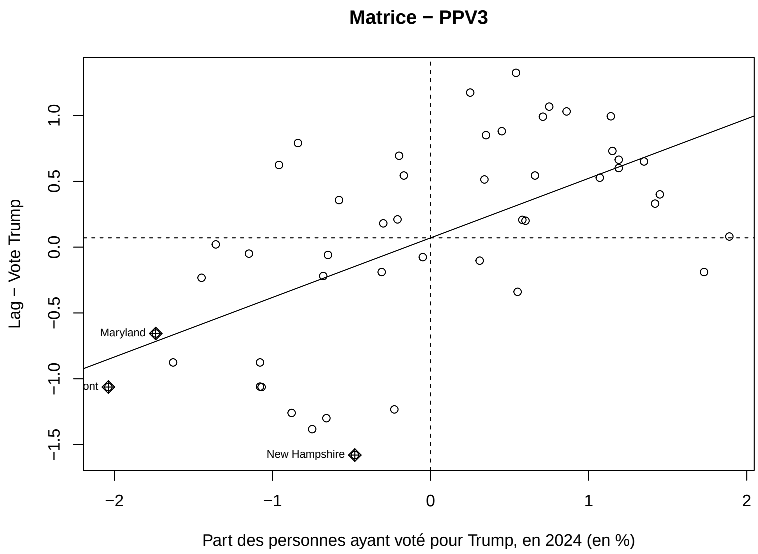


Figure 9: Moran index for the NN3 matrix

4.2 Measuring local spatial autocorrelation

The LISA (Local Indicators of Spatial Association) analysis applied to the results of the 2024 US presidential election, concerning the share of voters who voted for Donald Trump, enables us to explore the spatial dynamics of voting across the United States. Two spatial weighting matrices were used for this analysis: a queen-type matrix (considering States sharing a common border) and a matrix based on the 3 nearest neighbours.

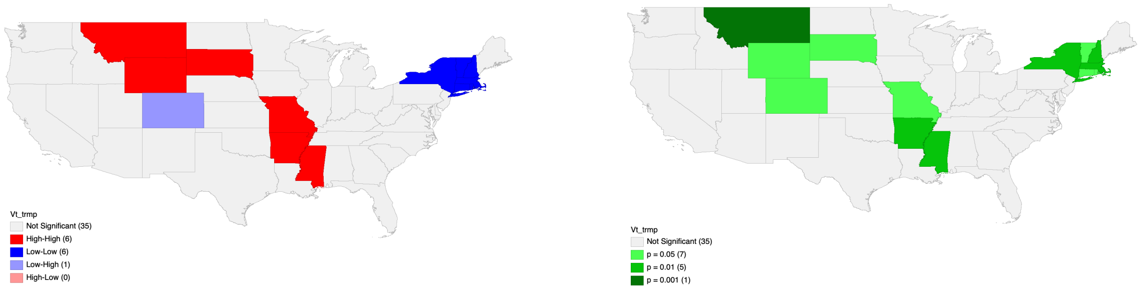


Figure 10: LISA and statistical significance of the queen weighting matrix

Figure 10 present a LISA analysis using a queen weighting matrix to examine spatial patterns of Trump vote share in the 2024 election.

- **High-High (H-H):** Wyoming, Montana, South Dakota, Missouri, Arkansas and Mississippi form significant clusters where high Trump vote percentages are surrounded by neighbors with similarly high values. This pattern is particularly pronounced in the Northern Plains region, suggesting strong regional support for Trump.
- **Low-Low (L-L):** New York, Vermont, New Hampshire, Massachusetts, Connecticut and Rhode Island displays a significant cold spot, with low Trump vote share surrounded by neighboring states with similarly low support. This reflects the consistent Democratic voting patterns in the Northeast.
- **Low-High (L-H):** Colorado stands as the only Low-High outlier, exhibiting relatively low Trump support despite being surrounded by states with higher vote shares. This political divergence aligns with Colorado's demographic shifts and higher education levels compared to neighboring states.
- **High-Low (H-L):** The analysis does not identify any significant High-Low outliers, suggesting the absence of states with unexpectedly high Trump support surrounded by low-support neighbors.

The significance map reveals Montana with the highest statistical significance ($p = 0.001$), while several Midwestern and Northeastern states show moderate significance levels ($p = 0.01$ or $p = 0.05$). States like Massachusetts, Vermont, Arkansas, and Mississippi display discernible spatial patterns at the $p = 0.05$ threshold. The majority of states show no statistically significant spatial autocorrelation in Trump voting patterns.

Figure 10 shows that the groupings observed are generally significant at the 0.05 threshold, with more robust points reaching 0.01 or 0.001.

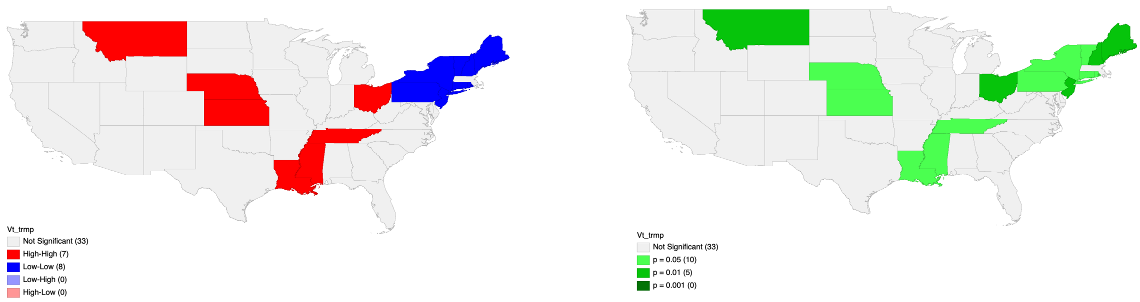


Figure 11: LISA et significativité pour la matrice des 3 plus proches voisins

The maps in Figure 11 present a LISA analysis employing a 3-nearest neighbors matrix to examine spatial patterns of Trump vote share in the 2024 election.

- **High-High (H-H):** Montana, Nebraska, Kansas, Ohio, Mississippi, Louisiana and Tennessee form significant clusters with high Trump vote percentages surrounded by neighbors with similarly high values. This pattern is particularly notable in the Great Plains region and parts of the South.
- **Low-Low (L-L):** The Northeast displays a significant cold spot, with New York, Vermont, New Hampshire, Massachusetts, Connecticut, Maine, New-Jersey, Pennsylvania and Rhode Island exhibiting low Trump vote share surrounded by neighbors with similarly low support. This pattern reflects the consistent Democratic voting patterns in densely populated urban areas of the Northeast.
- **Low-High (L-H):** No states display this pattern in the current analysis, suggesting the absence of significant political islands with unexpectedly low Trump support surrounded by high-support neighbors.
- **High-Low (H-L):** No states exhibit this pattern, indicating no areas where high Trump support is surrounded by notably lower support in neighboring states.

The significance map reveals five states with high statistical significance at the $p = 0.01$ level (Ohio, New Jersey, Massachusetts, Maine, and Montana), while ten states show moderate significance levels ($p = 0.05$), including Kansas, Tennessee, Mississippi, Alabama, Rhode Island, Connecticut, New York, Vermont, and Pennsylvania. The majority of states (33) show no statistically significant spatial autocorrelation in Trump voting patterns under this neighborhood definition. The change from a queen contiguity matrix to a 3-nearest neighbors approach reveals different spatial relationships, particularly strengthening the coherence of regional voting patterns in the Northeast.

5 Spatial model estimation

5.1 *Model selection*

This section examines the selection of the most appropriate spatial econometric models for analysing the determinants of votes for Donald Trump in the 2024 US presidential elections. Model selection is often based on the detection and quantification of spatial autocorrelation, i.e. the extent to which spatial observations are influenced by their neighbours. Common spatial models include the Spatial Error Model (SEM), the Spatial Lag Model (SLM), and the Spatial Lag Model with Spatial Errors (SDM). Each of these models attempts to capture different forms of spatial dependence, either in the errors or in the dependent variable itself.

Table III: Moran tests on OLS regression residuals

Weight matrix	Moran test on residuals				
	I observed	Expected value	Variance	z statistic	p-value
Queen	0,126	-0,063	0,008	2,083	0,037
Nearest neighbour	0,177	-0,063	0,030	1,382	0,167
3 nearest neighbours	0,149	-0,069	0,010	2,181	0,029

Table III presents the Moran tests applied to the residuals of the OLS regression model. Results reveal mixed evidence for the presence of residual spatial autocorrelation. The observed Moran index is positive for all weight matrices, suggesting some form of spatial clustering of the residuals. However, the statistical significance of these indices varies according to the matrix considered. For the Queen matrix, the observed Moran index is 0.126, with a z-statistic of 2.083 and a p-value of 0.037, indicating significant spatial autocorrelation at the p¡0.05 The three nearest neighbours matrix also produced a Moran index of 0.149, a z-statistic of 2.181 and a p-value of 0.029, confirming significant autocorrelation at p¡0.05.

However, for the nearest neighbour matrix, the p-value is 0.167, which does not allow us to reject the null hypothesis of no residual spatial autocorrelation at a conventional significance level. These results suggest that the OLS model may not capture properly the spatial dependence, especially for the neighbourhood structures defined by the Queen and nearest three neighbours matrices. The presence of spatial autocorrelation in the residuals indicates that the assumptions of the OLS model are not fully respected, which could bias the estimates and affect the validity of the statistical inferences. Therefore, it may be appropriate to consider more advanced spatial econometric models to account for these spatial effects not captured by the OLS model.

Table IV: Spatial dependency tests using different weight matrices

	Weight matrices : p-value		
Models	Queen	NN1	NN3
LMerr	0,2181	0,3168	0,1775
LMLag	0,0512	0,0389	0,0423
RLMerr	0,9096	0,6185	0,9376
RLMLag	0,1295	0,0610	0,1285

Table IV presents the results of the spatial dependence tests, evaluated using different weight matrices. The Lagrange multiplier tests (LMerr and LMLag) are used to determine whether the spatial autocorrelation is due to a dependency in the errors (LMerr) or in the dependent variable itself (LMLag). Robust versions of these tests (RLMerr and RLMlag) are used to take account of the potential presence of the other type of autocorrelation.

Looking at the p-values associated with each test and for each weight matrix, we observe that for the Queen matrix, the LMLag test displays a p-value of 0.0512, suggesting a spatial dependency at p¡0.1. The LMerr test has a p-value of 0.2181, indicating an absence of significant spatial dependency in the errors for this matrix. The RLMerr and RLMlag robust tests showed p-values of 0.9096 and 0.1295, respectively, which does not allow us to conclude that there is significant spatial dependence, either in the errors or in the dependent variable.

For the NN1 (nearest neighbour) matrix, the LMLag test gave a p-value of 0.0389, indicating significant spatial dependence at the 5% threshold. The LMerr test gives a p-value of 0.3168, suggesting that there is no significant spatial dependency in the errors. The RLMerr and RLMlag robust tests had p-values of 0.6185 and 0.0610, respectively, suggesting no significance for RLMerr, but significance at p¡0.1 for RLMlag.

Finally, for the NN3 matrix (3 nearest neighbours), the LMLag test showed a p-value of 0.0423, indicating significant spatial dependence at the 5% threshold. The LMerr test shows a p-value of 0.1775, which does not allow us to conclude that there is a significant spatial dependency in the errors. The RLMerr and RLMlag robust tests showed p-values of 0.9376 and 0.1285, indicating an absence of significance for RLMerr, but not for RLMlag.

Given that none of the robust tests is significant (only the LMLag test is significant), it is appropriate to consider a SLX (Spatial Lag of X) model and compare it with an SDM (Spatial Durbin Model). This approach is based on the methodology of Elhorst (2010). The analysis begins with ordinary least squares (OLS) estimation, followed by LM robustness tests (RLMerr and RLMlag), which are not significant here. Next, the SLX model is estimated by including the spatially lagged explanatory variables (WX). If the associated coefficients (θ) are insignificant ($\theta = 0$), the OLS model is sufficient. Otherwise, an SDM model is estimated.

Table V: Coefficients and p-values for SLX models

Variable	SLX - Queen		SLX - NN3	
	Estimate	$Pr(>\|t\|)$	Estimate	$Pr(>\|t\|)$
(Intercept)	29.350	0.790	-45.710	0.652
GDP	-0.00386	0.0663	-0.00260	0.223
Legal Residents	0.00121	0.188	0.00068	0.449
Hispanic share	-0.2319	0.143	-0.09749	0.543
Black share	-0.2874	0.132	-0.1300	0.493
Education	-1.283	1.76e-7	-1.446	6.54e-6
Gender ratio	0.817	0.218	0.9805	0.150
Variable	**SLX - Queen**		**SLX - NN3**	
Spatial Lag	Estimate	$Pr(>\|t\|)$	Estimate	$Pr(>\|t\|)$
GDP	-0.01881	0.0026	-0.01388	0.032
Legal residents	0.002674	0.214	0.001829	0.322
Hispanic population	0.2376	0.314	-0.1264	0.587
Black population	0.5210	0.144	0.4077	0.238
Education	-0.4050	0.284	-0.1254	0.670
Gender ratio	0.01570	0.988	0.5928	0.602
Overall p-value	1,41 $\times 10^{-9}$	-	1,21 $\times 10^{-8}$	-

Analysis of the SLX models with the Queen and NN3 weight matrices provides some insight on the spatial factors associated with the Trump vote. For the SLX model based on the Queen-type adjacency matrix, only the education shows a significant and negative direct effect ($Estimate$ = -1.283, $p < 0.001$), suggesting that an increase in the level of education is associated with a decrease in the Trump vote in the state under consideration. In addition, the lagged variable is also significant ($Estimate$ = -0.01881, $p = 0.0026$), indicating that a higher GDP in surrounding states is associated with a decrease in the Trump vote in the state under consideration.

However, for the SLX model with the 3 nearest neighbours matrix (NN3), only the direct effect of the education variable remained significant ($Estimate$ = -1.446, $p < 0.001$), reinforcing the importance of this variable. The lagged variable is significant at the 5% threshold ($Estimate$ = -0.01388, $p = 0.032$). The other variables, both direct and spatially lagged, were not statistically significant, suggesting a limited impact of these factors on the dependent variable in the SLX models considered.

Moreover, the extremely low overall p-values (1.4110^{-}9 for the Queen model and 1.2110^{-}8 for the NN3 model) indicate a very high overall significance of the models, confirming that all the explanatory variables, including their spatial lags, contribute significantly to explaining the variance in the percentage of votes for Trump in 2024 at the state level.

It is important to note that if only one lagged variable is significant in the SLX model, we should consider comparing this model with an SDM model. The comparison between SLX and SDM is made using a likelihood ratio test (LR). If LR exceeds the critical value, the SDM is preferred; otherwise, the SLX is selected. The lack of significance in the robust tests suggests that spatial effects are better captured by lagged explanatory variables rather than by direct autocorrelation.

Comparaisons	**Queen**	**NN3**
SAR vs SLX	0.002***	0.042**
SAR vs SDM	0.005***	0.012**
SLX vs SDM	0.956	0.027**

Significativité : *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table VI: Results of likelihood ratio tests

The analysis of the likelihood ratio (LR) tests provides important indications for the choice of the most appropriate spatial model, in addition to the previous SLX results.

- **Queen adjacency matrix :**
  - The SAR vs SLX and SAR vs SDM comparisons are significant at the 1% level ($p < 0.01$), indicating that there is a significant difference between the SAR model and the SLX and SDM models. This suggests that the introduction of exogenous spatial effects (SLX) or a combination of exogenous and endogenous effects (SDM) significantly improves the fit of the model compared with a simple autoregressive model (SAR).
  - The SLX vs SDM comparison is not significant ($p = 0.956$), which suggests that there is no significant difference between the SLX and SDM models in this case. Given that the SLX model is more parsimonious (fewer parameters), it would be preferable to retain the SLX model.
- **3 nearest neighbours matrix (NN3) :**
  - The SAR vs SLX and SAR vs SDM comparisons are significant at the 5% level ($p < 0.05$), which indicates, as for the Queen matrix, that the SLX and SDM models offer a better fit than the SAR model.
  - The SLX vs SDM comparison is significant at the 5% level ($p = 0.027$), which suggests that the SDM model significantly improves the fit compared with the SLX model. In this case, the SDM model should be preferred. By incorporating both spatially lagged explanatory variables and a spatially lagged dependent variable, an SDM model can capture more complex spatial dependence mechanisms.

In summary, for the Queen matrix, the SLX model is the preferred choice, while for the NN3 matrix, the SDM model seems the most appropriate.

Models	Queen	NN3
SAR	311.2218	310.5479
SLX	302.7384	309.0330
SDM	304.7354	306.1716

Table VII: Comparison of AIC criteria

Analysis of the Akaike Information Criteria (AIC) completes the interpretation of the spatial models, taking into account both the goodness of fit and the parsimony of the models. A lower AIC indicates a better compromise between these two aspects. By linking these results to the likelihood ratio tests and the previous SLX results, we can refine the choice of the most appropriate model.

- **Queen adjacency matrix :**
  - The SLX model has the lowest AIC (302.7384) compared with the SAR (311.2218) and SDM (304.7354) models.
  - This result, combined with the non-significant likelihood ratio test between SLX and SDM ($p = 0.956$), confirms that the SLX model is the most appropriate for the Queen matrix. Although the LR test indicated a significant improvement over the SAR model, the SDM model does not provide a significant improvement over the SLX model, and its higher AIC justifies preferring the simpler SLX model.
  - In the SLX model, only the education variable has a significant and negative direct effect ($Estimate$ = -1.283, $p < 0.001$), and the lagged GDP variable is also significant ($Estimate$ = -0.01881, $p = 0.0026$).
- **Matrix of the 3 nearest neighbours (NN3) :**
  - The SDM model has the lowest AIC (306.1716) compared with the SAR (310.5479) and SLX (309.0330) models.

- This result, combined with the significant likelihood ratio test between SLX and SDM ($p = 0.027$), confirms that the SDM model is the most appropriate for the NN3 matrix. The SDM model significantly improves the fit compared with the SLX model, and its lower AIC justifies its preference.
- In the SLX model, only the direct effect of the education variable remains significant ($Estimate$ = -1.446, $p < 0.001$) and lagged GDP is significant at the 5% threshold ($Estimate$ = -0.01388, $p = 0.032$). The improvement provided by the SDM model suggests that more complex spatial dependence mechanisms are at work, justifying the inclusion of a spatially lagged dependent variable.

In conclusion, based on the likelihood ratio tests and the AIC criteria, the SLX model is preferable for the Queen adjacency matrix, while the SDM model is preferable for the 3 nearest neighbours (NN3) matrix.

5.1.1 Model interpretation

Table VIII: Spatial Lag X (SLX) Regression Model Results

Variable	**Coefficient**	**Std. Error**	**t-value**	**p-value**
Main Effects				
Intercept	29.350	109.400	0.268	0.790
GDP	-0.004	0.002	-1.896	0.066
Legal Residents	0.001	0.001	1.342	0.188
Hispanic Population	-0.232	0.155	-1.499	0.143
Black Population	-0.287	0.186	-1.544	0.132
Education	-1.283	0.198	-6.489	<0.001***
Gender Ratio	0.817	0.651	1.254	0.218
Spatial Lag Effects				
GDP	-0.019	0.006	-3.249	<0.003**
Legal Residents	0.003	0.002	1.265	0.214
Hispanic Population	0.238	0.232	1.022	0.314
Black Population	0.521	0.349	1.493	0.144
Education	-0.405	0.372	-1.088	0.284
Gender Ratio	0.016	1.100	0.014	0.989
Model Diagnostics				
Model p-value		1.41×10^{-9}***		
Log-Likelihood		-137.369		
Akaike Information Criterion (AIC)		302.738		
Degrees of Freedom		14		

Table IX: Spatial Durbin Model Regression Results

Variable	Coefficient	Std. Error	z-value	p-value
Main Effects				
Intercept	-33.670	80.235	-0.420	0.675
GDP	-0.002	0.002	-1.037	0.300
Legal Residents	0.001	0.001	1.034	0.301
Hispanic Population	-0.154	0.126	-1.224	0.221
Black Population	-0.201	0.152	-1.327	0.185
Education	-1.430	0.217	-6.583	<0.001***
Gender Ratio	0.770	0.534	1.442	0.149
Spatial Lag Effects				
GDP	-0.014	0.005	-2.776	<0.006**
Legal Residents	0.002	0.001	1.214	0.225
Hispanic Population	-0.003	0.189	-0.014	0.989
Black Population	0.413	0.270	1.531	0.126
Education	0.393	0.292	1.345	0.179
Gender Ratio	0.269	0.909	0.296	0.767
Spatial Autocorrelation				
ρ (Spatial Autocorrelation)	0.400	0.139	2.870	0.004**
Model Diagnostics				
Log Likelihood		-138.086		
AIC		306.17		
Model p-value		0.027**		

The results present the estimation of two spatial econometric models, a Spatial Durbin Model (SDM) and a Spatial Lag X Model (SLX). The aim is to identify local factors and the spatial influences of neighbouring units on the share of people who voted for Trump in 2024.

Regarding the main effects, the estimation reveals that the education has a negative and statistically significant coefficient in both models (SDM: $\beta = -1.430, p < 0.001$; SLX: $\beta = -1.283, p < 0.001$). This result suggests that a higher level of education within a spatial unit is associated with a decrease in the share of people who voted for Trump, in 2024 from this same unit, all other things being equal. The coefficients of the other main explanatory variables are not statistically significant at the conventional thresholds in either model, indicating that there is no significant direct local effect of these variables on the share of people who voted for Trump in 2024.

Analysis of the spatial lag effects shows that the coefficient of spatially lagged GDP is negative and significant in both models (SDM: $\gamma = -0.014, p = 0.006$; SLX: $\gamma = -0.019, p = 0.003$). This finding indicates that the level of GDP in neighbouring spatial units has a significantly negative impact on the share of people who voted for Trump in 2024 in the spatial unit. The coefficients of the other spatially lagged explanatory variables are not statistically significant in either model, suggesting a limited indirect spatial influence of these factors.

Within the SDM model, the ρ parameter measuring the spatial autocorrelation of the share of people who voted for Trump in 2024 (in %) is positive and significant ($\rho = 0.400, p = 0.004$), highlighting the presence of positive spatial dependence where similar values of the share of people who voted for Trump in 2024 tend to cluster geographically. The SLX model does not include a spatial autoregressive term for the share of people who voted for Trump in 2024, focusing solely on the impact of lagged explanatory variables.

In terms of model diagnostics, the SDM model has a log-likelihood of -138.086 and an Akaike Information Criterion (AIC) of 306.17, with an overall model p-value of 0.027. The SLX model has a log-likelihood of -137.369 and an Akaike information criterion (AIC) of 302.738, with an overall p-value of $\mathbf{1.41 \times 10^{-9}}$. The SLX model uses 14 degrees of freedom. The overall significance of the two models indicates that they explain a significant proportion of the variance in the share of people who voted for Trump in 2024, taking account of local and/or spatial effects. The lower AIC of the SLX model suggests a better fit of the data compared to the SDM model. The extremely low overall p-value of the SLX model reinforces the conclusion that the model as a whole is statistically significant.

In conclusion, the combined estimation of the SDM and SLX models reveals a significant and negative local influence of the level of education on the proportion of people who voted for Trump in 2024. In addition, both models show a significant and negative indirect spatial effect of GDP in neighbouring areas. The presence of a positive spatial autocorrelation in the share of people voting for Trump in 2024 , captured by the SDM model, reinforces the importance of considering spatial interdependencies. The SLX model, with its lower AIC and highly significant overall p-value, seems to offer a better representation to explain the share of votes for Trump in 2024.

Table X: Impact Measures (SLX, Queen)

Variable	**Direct**	**Indirect**	**Total**
GDP	-0.004	-0.019	-0.023
Legal Residents	0.001	0.003	0.004
Hispanique population	-0.232	0.238	0.006
Black population	-0.287	0.521	0.234
Education	-1.283	-0.405	-1.688
Gender ratio	0.817	0.016	0.833

Academic interpretation of the SLX model's impact measures (Table X) with the Queen-type adjacency matrix reveals that GDP has a negative direct effect of -0.004, suggesting that a one billion increase in GDP in one state is associated with a small decrease in the dependent variable in that same state. The indirect effect is also negative and larger (-0.019), indicating that an increase in GDP in neighbouring states is associated with a more substantial decrease in the dependent variable in the state under consideration. The total effect is therefore negative (-0.023). Concerning the number of legal residents, the direct effect is positive (0.001), as is the indirect effect (0.003), resulting in a positive total effect (0.004), although of small magnitude. The Hispanic population share shows a negative direct effect (-0.232) but a positive indirect effect (0.238), leading to a total effect of almost zero (0.006), suggesting compensatory spatial dynamics where a negative local effect is counterbalanced by a positive effect from neighbouring areas. The African-American population share has a negative direct effect (-0.287) and a larger positive indirect effect (0.521), leading to a positive total effect (0.234), indicating that the African-American share in neighbouring states has a stronger positive influence than in the state itself. The education variable shows a significant negative direct effect (-1.283) and an equally negative indirect effect (-0.405), leading to a substantial negative total effect (-1.688), suggesting that a higher share of the population with a certain level of education has a negative impact on the dependent variable, both locally and in neighbouring states. Finally, the male/female ratio has a positive direct effect (0.817) and a weakly positive indirect effect (0.016), resulting in a positive total effect (0.833).

Table XI: Impact Measures (SDM, NN3)

Variable	**Direct**	**Indirect**	**Total**
GDP	-0.004	-0.022	-0.026
Legal Residents	0.001	0.003	0.004
Hispanique population	-0.163	-0.099	-0.262
Black population	-0.159	0.512	0.353
Education	-1.452	-0.276	-1.728
Gender Ratio	0.843	0.889	1.732

For the SDM model (Table XI with the 3 nearest neighbours matrix, GDP shows a negative direct effect of -0.004 and a larger negative indirect effect of -0.022, resulting in a negative total effect of -0.026 . Legal residents have a positive direct effect (0.001) and an equally positive indirect effect (0.003), with a positive total effect of 0.004, similar to the SLX model. The share of the Hispanic population has a negative direct effect (-0.163) and an equally negative indirect effect (-0.099), unlike the SLX model where the indirect effect was positive, giving a negative total effect of -0.262 . The share of the African-American population has a negative direct effect (-0.159) and a substantial positive indirect effect (0.512), resulting in a total positive effect of 0.353, a trend similar to that observed in the SLX model, although the magnitudes differ slightly. The education variable shows a significant negative direct effect (-1.452) and a negative indirect effect (-0.276), leading to a significant negative total effect (-1.728), with slightly more pronounced values in absolute terms than in the SLX model.The male/female ratio shows a positive direct effect (0.843) and a significant positive indirect effect (0.889), leading to a higher positive total effect (1.732) compared with the SLX model, suggesting a stronger spatial influence of this ratio in the SDM model with a neighbourhood definition based on the nearest k.

6 Conclusion

The purpose of this study was to examine whether education atteinment can explain Trump's electoral success in the 2024 U.S. presidential election, while accounting for spatial dependencies between states. Prior research has consistently shown a negative correlation between education and Republican voting, suggesting that individuals with higher levels of education are more likely to support Democratic candidates. However, given shifts in voting patterns and Trump's increasing appeal among minority voters, the persistence of this relationship needed further investigation. To this end, the study employed spatial econometrics to assess whether education remained a robust predictor of Trump's vote share after controlling for economic and demographic factors.

The descriptive analysis revealed clear regional disparities in education levels, with coastal and urban states displaying significantly higher levels of education compared to rural and Southern states. This pattern largely mirrored the spatial distribution of Trump's vote, reinforcing the idea that education plays a central role in shaping electoral preferences. However, the analysis also highlighted that education is not the unique determinant of voting behavior, as economic and demographic factors influence electoral outcomes in complementary ways.

Econometric results confirmed that education was negatively correlated with Trump support, consistent with previous findings. However, spatial models demonstrated that this effect was not uniform across states. The spatial lag of education was significant, suggesting that a state's level of education not only affects its own voting behavior but also influences neighboring states. This highlights the importance of regional spillover effects, where states with higher educational attainment tend to be surrounded by states that also vote less for Trump.

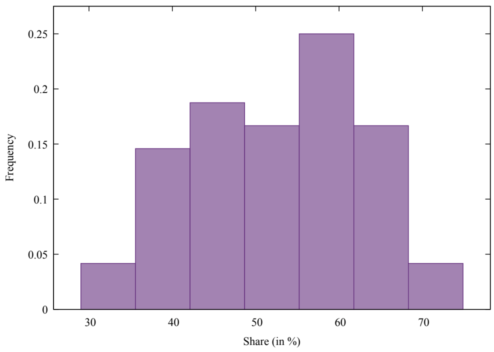
The role of economic factors was more complex. While GDP was negatively correlated with Trump voting, the spatial models indicated that its effect was weaker than that of education and varied across states. This suggests that economic inequality alone does not fully explain Republican support, but may interact with structural factors such as race and education (Autor et al., 2016). Similarly, demographic variables showed the expected trends: a higher proportion of Black and Hispanic residents was associated with lower Trump support, yet the effect was weaker than in previous elections, reflecting Trump's growing appeal among minority voters. The gender ratio, on the other hand, had a positive and significant effect, confirming that states with more men than women were more likely to support Trump, a finding consistent with research on gender and political conservatism (Inglehart and Norris, 2000).

These results reinforce the importance of education in shaping political behavior, but also demonstrate that its effects are spatially dependent. The presence of regional spillovers suggests that political preferences are not determined in isolation, but are influenced by broader geographic and socio-economic contexts. Ignoring spatial dependencies, as is often the case in traditional electoral studies, can lead to misinterpretations of causal relationships, reinforcing the necessity of spatial econometrics in political science research.

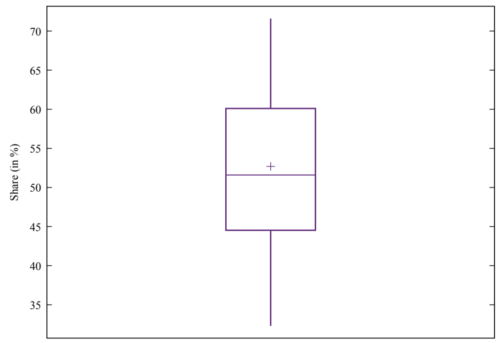
Overall, this study provides new insights into the geographic dynamics of electoral behavior, demonstrating that education remains a central determinant of Trump's vote share, but its effects are context-dependent. The findings suggest that policies aimed at improving access to higher education could have long-term electoral implications, particularly in regions with low educational attainment. Future research could refine these conclusions by exploring more granular spatial units, such as counties or metropolitan areas, to further investigate the localized effects of education on voting behavior.

7 Appendix

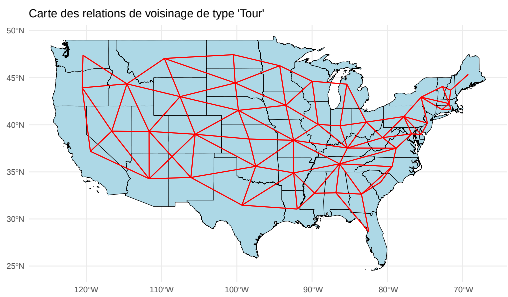
Figure 12: Distribution of Trump's vote



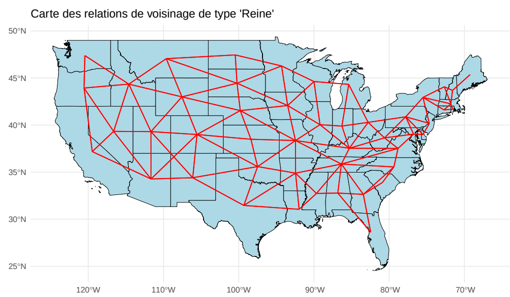
(a) Histogram



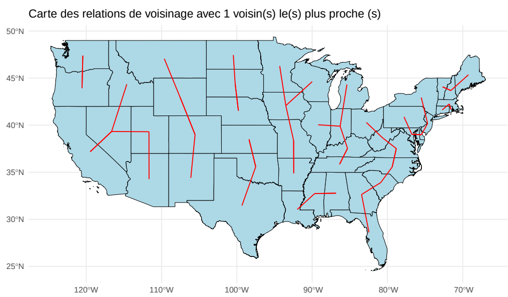
(b) Boxplot



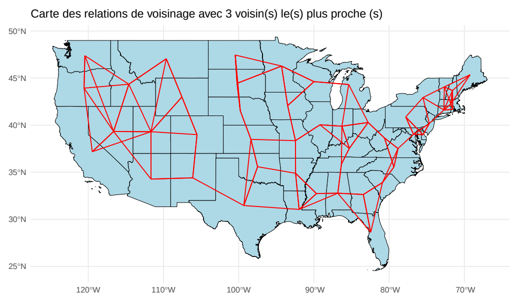
(a) Map of neighborhood relations of type 'Rook'



(b) Map of neighborhood relations of type 'Queen'



(c) Map of neighborhood relations with 1 nearest neighbor



(d) Map of neighborhood relations with 3 nearest neighbors

Figure 13: Different types of neighborhood relations

7.1 Geoda

- Charger le fichier shp
- Tools –¿ Weight Manager –¿ Create
- Prendre la variable Trump en ID
- Queen Contiguity (Order of contiguity : 1), ou sinon pour les autres cas Distance Weight –¿ K-Nearest Neighbors et prendre 1 ou 3 en fonction de 1PPV ou 3PPV)

- Attention: on peut sélectionner "Use inverse distance" si l'on souhaite afficher avec l'effet 1/distance
- A chaque fois il faudra sauvegarder au format gwt
- On peut afficher les graphiques des matrices avec connectivity map en sélectionnant la matrice que l'on souhaite afficher
- Ensuite, pour chaque matrices Space–¿ Univariate Local Moran's I
- Cocher les trois options afin d'obtenir les trois graphiques
- Il ne reste plus qu'à sauvegarder les graphiques

References

Abrajano, M., & Hajnal, Z. (2015). *White backlash: Immigration, race, and american politics.* Princeton University Press.

Autor, D. H., Dorn, D., & Hanson, G. H. (2016). The china shock: Learning from labor-market adjustment to large changes in trade. *Annual review of economics*, *8*(1), 205–240.

Borjas, G. J. (2018). The economics of immigration. In *The new immigrant in the american economy* (pp. 1–52). Routledge.

Center, P. R. (2018). Wide gender gap, growing educational divide in voters' party identification [https://www.pewresearch.org/politics/2018/03/20/wide-gender-gap-growing-educational-divide-in-voters-party-identification/].

Corral, Á. J., & Leal, D. L. (2020). Latinos por trump? latinos and the 2016 presidential election. *Social Science Quarterly*, *101*(3), 1115–1131.

Dawson, M. C. (1995). *Behind the mule: Race and class in african-american politics.* Princeton University Press.

Fujiwara, T., Muller, K., & Schwarz, C. (2020). How twitter affected the 2016 presidential election. *Vox EU.*

Hainmueller, J., & Hopkins, D. J. (2014). Public attitudes toward immigration. *Annual review of political science*, *17*(1), 225–249.

Inglehart, R., & Norris, P. (2000). The developmental theory of the gender gap: Women's and men's voting behavior in global perspective. *International Political Science Review*, *21*(4), 441–463.

Kaufman, S. B., Quilty, L. C., Grazioplene, R. G., Hirsh, J. B., Gray, J. R., Peterson, J. B., & DeYoung, C. G. (2016). Openness to experience and intellect differentially predict creative achievement in the arts and sciences. *Journal of personality*, *84*(2), 248–258.

Lassalle, T. (2023). La question raciale et le vote républicain. *La Vie des Idées.*

Margalit, Y. (2019). Economic insecurity and the causes of populism, reconsidered. *Journal of Economic Perspectives*, *33*(4), 152–170.

Peri, G. (2012). The effect of immigration on productivity: Evidence from us states. *Review of Economics and Statistics*, *94*(1), 348–358.

Philpot, T. S. (2018). Race, gender, and the 2016 presidential election. *PS: Political Science & Politics*, *51*(4), 755–761.

Pop, M.-I., & Ene, I. (2019). Influence of the educational level on the spreading of fake news regarding the energy field in the online environment. *Proceedings of the International Conference on Business Excellence*, *13*(1), 1108–1117.

Schaffner, B. F., MacWilliams, M., & Nteta, T. (2018). Understanding white polarization in the 2016 vote for president: The sobering role of racism and sexism. *Political Science Quarterly*, *133*(1), 9–34.

Western, B., & Pettit, B. (2010). Incarceration & social inequality. *Daedalus*, *139*(3), 8–19.